Paper:

Effects of a Novel Sympathy-Expression Method on Collaborative Learning Among Junior High School Students and Robots

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In recent years, educational-support robots, which are designed to aid in learning, have received significant attention. However, learners tend to lose interest in these robots over time. To solve this problem, researchers studying human-robot interactions have developed models of emotional expression by which robots autonomously express emotions. We hypothesize that if an educational-support robot uses an emotion-expression model alone and expresses emotions without considering the learner, then the problem of losing interest in the robot will arise once again. To facilitate collaborative learning with a robot, it may be effective to program the robot to sympathize with the learner and express the same emotions as them. In this study, we propose a sympathy-expression method for use in educational-support robots to enable them to sympathize with learners. Further, the effects of the proposed sympathy-expression method on collaborative learning among junior high school students and robots are investigated.

Keywords: educational-support robots, sympathy expression method, collaborative learning, human-robot interaction

1. Introduction

The growth of robotic technology has prompted the development of educational-support robots to assist learning. Recent studies have reported that the use of robots is beneficial to children's learning. For example, Shiomi et al. [1] investigated whether a social robot can stimulate scientific curiosity in elementary school children. A robot was installed in a science classroom for one month, and the children were allowed to freely interact with it during breaks. Although the robot did not encourage all the children to learn science, children who posed science questions to the robot became more interested in the subject. Kanda et al. [2] examined the hypotheses that robots can form relations with children and that children may learn from robots as they learn from other children. The results of this study suggested that interactive robots should be designed to have something in common with their users, presenting both a social and a technical challenge.

The problem associated with these robots is that children gradually lose interest in the robots as learning progresses [2, 3]. In another study, college students were initially interested in the robot but began to neglect it as their learning progressed [4]. This study focuses on emotion expression methods that educational-support robots use to foster user familiarity, thereby addressing the problem of the gradual reduction in the rate of learning over the course of the learning process. This emotion-expression method was designed to be used either by a screen agent or by a robot programmed to express seemingly autonomous emotions. Previous studies dealing with human-robot interactions have reported the effects of using robots programmed with emotion-expression models. For example, Wada et al. [5] reported a pet robot that could elicit a feeling of familiarity in a user by expressing seemingly autonomous emotions. Felix et al. [6] reported that emotion-expression methods are beneficial for human-agent interactions because they catalyze more effective interactions with humans than models that express random emotions.

However, we hypothesize that if a robot uses an emotion-expression method alone and expresses its emotions without considering the learner in educational-support robots, then the problem of losing interest in the robot will arise once again. To facilitate collaborative learning with a robot, it can be effective to program the robot to sympathize with the learner and express the same emotions as they do. Iolanda et al. [7] reported that robots which sympathize with children had a positive impact in terms of the long-term interactions between the children and the robots. Many previous studies focused on the effect between robots and elementary school students. Few of them investigated a method by which a robot sympathizes with junior high school students during collaborative learning. Moreover, few studies reported the potential effect of collaborative learning between junior high school students and the robot which sympathize with them.

Therefore, in this study, we propose a sympathy expres-

sion method for educational support robots to enable them to express sympathetic emotions during interacting with learners. Moreover, the effect of our sympathy expression method was examined when applying to collaborative learning among junior high school students and the robot. In this study, we defines collaborative learning as the one in which learners and robots alternately solve problems. Our sympathy expression method relies on Russell's circumplex model of affect [8] in which the emotional state is described on two dimensions: pleasure-displeasure and arousal-sleep. Emotions of sympathy with the learner's emotions are represented by two emotion vectors. The correct and incorrect emotion vectors represent the robot's emotions when the learner's answers are correct and incorrect, respectively. Moreover, the lengths and angles of the emotion vectors are updated according to the number of correct answers and the answer time of the learner (i.e., the time required by a learner to answer a question). In this way, our sympathy-expression method can guide the robot to express multiple emotions and sympathy to the learner's learning situation.

2. Relevant Studies

Previous studies dealing with human-robot interactions have examined several situations of interaction between humans and robots [9, 10]; we focus on the study of a robot that can be used in a school or other educational setting. For example, Suzuki and Kanoh [11] reported the implementation of a robot function for nodding and providing verbal hints, which is otherwise used in expression education. In addition to providing support by giving verbal hints, the robot nods and gives the impression that it is evaluating the learner's expression activity to improve their learning motivation. The results suggest that there is a possibility that a learning effect similar to that of a human instructor can be achieved when the robot used in support expression-based education provides not only hints to support the learner but also nods to express evaluation. Okazaki et al. [12] investigated the behavior of a human teaching a robot and that of the robot learning from a human, both of which are necessary for the development of a pedagogical relation. The results of the study found that because the robot made mistakes repeatedly in doing what it learned from the person, the person became more careful in teaching the former so as to enhance its understanding. It was also observed that when the robot expressed how much it understood, the person attempted to confirm it.

Other studies have investigated the effects of the robots which sympathize with users. For example, Cramer et al. [13] investigated how sympathy affects people's attitudes toward robots. In their study, two groups of participants watched a four-minute video with an actor playing a cooperative game with an iCat robot. For one group, the robot expressed accurate empathetic behavior toward the actor; in the other, the robot's empathetic behavior was incongruent. A significant negative effect on users' trust was observed under the inaccurate empathic-behavior condition. Conversely, participants who observed the robot displaying accurate empathic behavior perceived their relation with the robot to be closer. In another study [14], a robot with the form of a chimpanzee head mimicked the user's mouth and head movements, the authors found that most subjects considered this interaction to be more satisfactory than interactions in which the robot lacked mimicking capabilities. Moreover, Iolanda et al. [7] reported that a robot which sympathizes with children had a positive impact in terms of the long-term interaction between the children and the robots.

However, none of the previous studies report on collaborative learning in which the learner and the robot alternately solve problems. To address this gap, we propose a sympathy-expression method for educational-support robots that can enable robots to sympathize with learners during collaborative learning. Such a method has not been previously used.

3. Sympathy Expression Method

3.1. Russell's Circumplex Model of Affect

In the conventional method [15], emotions are expressed using an environment-adaptive action selection system called the urge system [16]. However, a robot using the conventional model [15] tends to repeatedly express the same emotion because the decision-making phase is conclusive. To solve this problem, a previous study proposed an emotion-expression method based on Russel's circumplex model of affect [8], which promotes more effective interaction than the conventional method [6]. Therefore, Russell's circumplex model of affect is adopted in the present study.

3.2. Proposed Method

The proposed method involves expressing emotions by two emotion vectors, enabling the robot to actively sympathize with the learner (see **Fig. 1**): $\vec{A}$ is defined as the correct emotion vector, which represents the emotion when the answer is correct; $\vec{B}$ is defined as the incorrect emotion vector corresponding to a wrong answer. The $L_{\vec{A}}$ of $\vec{A}$ lies between 0 and 1.0 and $\theta_{\vec{A}}$ ranges from $-\frac{\pi}{2}$ to $\frac{\pi}{2}$. Meanwhile, the $L_{\vec{B}}$ of $\vec{B}$ lies between 0 and 1.0 and $\theta_{\vec{B}}$ ranges from $-\frac{\pi}{2}$ to $\frac{\pi}{2}$. $L\cos\theta$ and $L\sin\theta$ correspond to pleasure-displeasure and arousal-sleep, respectively. The emotion vectors, $\vec{A}$ and $\vec{B}$, vary as follows:

$$
\begin{aligned}
&if(\text{Learners solved question correctly})\\
&\quad L_{\vec{A}} \leftarrow L_{\vec{A}} + 0.2\\
&\quad L_{\vec{B}} \leftarrow L_{\vec{B}} - 0.2\\
&else\\
&\quad L_{\vec{A}} \leftarrow L_{\vec{A}} - 0.2\\
&\quad L_{\vec{B}} \leftarrow L_{\vec{B}} + 0.2\\
&(0 \leq L_{\vec{A}} \leq 1.0,\ 0 \leq L_{\vec{B}} \leq 1.0)
\end{aligned}
$$

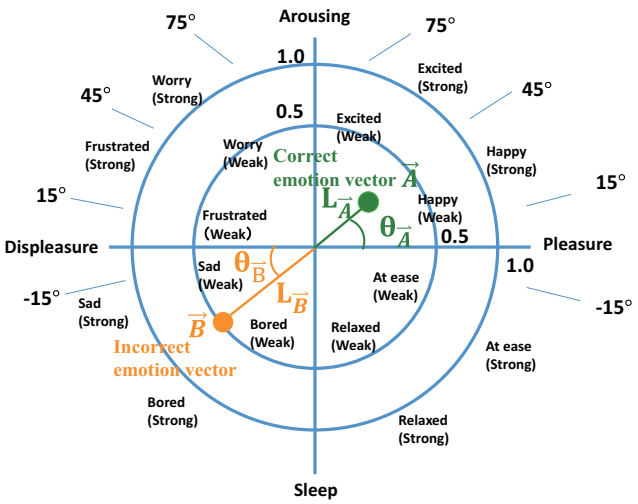


Fig. 1. Proposed method.

$$
\begin{aligned}
&if(\text{Answer time} < \text{Basic time})\\
&\quad if(\text{Learners solved the question correctly})\\
&\qquad \theta_{\vec{A}} \leftarrow \theta_{\vec{A}} + \tfrac{\pi}{12}\\
&\quad else\\
&\qquad \theta_{\vec{B}} \leftarrow \theta_{\vec{B}} + \tfrac{\pi}{12}\\
&else\\
&\quad if(\text{Learners solved the question correctly})\\
&\qquad \theta_{\vec{A}} \leftarrow \theta_{\vec{A}} - \tfrac{\pi}{12}\\
&\quad else\\
&\qquad \theta_{\vec{B}} \leftarrow \theta_{\vec{B}} - \tfrac{\pi}{12}\\
&\left(-\tfrac{\pi}{2} \le \theta_{\vec{A}} \le \tfrac{\pi}{2}, -\tfrac{\pi}{2} \le \theta_{\vec{B}} \le \tfrac{\pi}{2}\right)
\end{aligned}
$$

The optimal combination of these parameters ($L \pm 0.2$ and $\theta \pm \frac{\pi}{12}$) for the proposed method was determined from the results of simulation experiments. The learning data was used in the simulation experiments to compare all combination of the parameters ($L \pm 0.2, 0.3, 0.4$ and $\theta \pm \frac{\pi}{18}, \frac{\pi}{12}, \frac{\pi}{9}$) for the proposed method. The learning data consisted of the one obtained from ten learners solving 20 questions in the learning system. Information regarding correct/incorrect answers and learner's answer time for each question was also included in the learning data. The number of "emotion expressed times" and "emotion changed times" was also counted by the simulation experiments. The emotion expressed times were defined as the number of different emotions which were expressed by the robot with each model in each learning section. The emotion changed times were defined as the number of times the robot expressed emotions except those expressed for the previous question. High numbers of both indicated that the robot was able to express multiple emotions instead of expressing uniform emotions.

The results of the simulation experiments suggested that the emotion expressed times and emotion changed times were higher in the proposed model which used the combination of the parameters ($L \pm 0.2$ and $\theta \pm \frac{\pi}{12}$) than the combinations of other parameters. Thus, we believe that a robot using the proposed model, which used the optimal combination of parameters ($L \pm 0.2$ and $\theta \pm \frac{\pi}{12}$), can express multiple emotions in a collaborative human-learning environment instead of expressing uniform emotions.

The answer time is defined as the time required by a learner to answer a question, and the basic time describes the previous answer time. For the first question, the basic time is set to the average answer time in the previous learning session.

In the proposed method, twenty-four emotions (12 strong, 12 weak) are arranged at 30° intervals in a two-dimensional plane following Russell's circumplex model. The 12 weak emotions are plotted inside a circle of radius 0.5 in this plane, while the 12 strong emotions are plotted outside a circle of radius 0.5 and inside a circle of radius 1.0. The emotion to be expressed is determined by the lengths L and angles θ of the emotion vectors, A and B. The emotions are arranged at 30° intervals and have ranges of $\pm 15°$; hence, by the proposed method, if an emotion vector is mapped into the range of a given emotion, then that emotion is expressed. For example, if the angle θ of emotion vector A is within $15° < \theta_{\vec{A}} \le 45°$, the "happy" emotion is expressed. If the angle θ of emotion vector B is within $-45° < \theta_{\vec{B}} \le -15°$, the "sad" emotion is expressed. The strength of the emotion corresponds to by the length L of the emotion vector: if L is less than 0.5, it is a "weak" emotion, whereas if L is greater than 0.5, it is a "strong" emotion.

Fig. 2. Appearance of Ifbot.

4. Overview of the Robot

4.1. Using the Robot

The robot used in this study was an Ifbot (**Fig. 2**), which is a conversational robot. Ifbot is able to express 24 expressions and does not move its arms or its body. The proposed learning system is integrated into Ifbot such that Ifbot can operate simultaneously with the learning system. This study examines how long learners continue to learn with the robot according to the proposed method. Therefore, the robot does not use a function that would enable it to interact with a human directly, such as voice

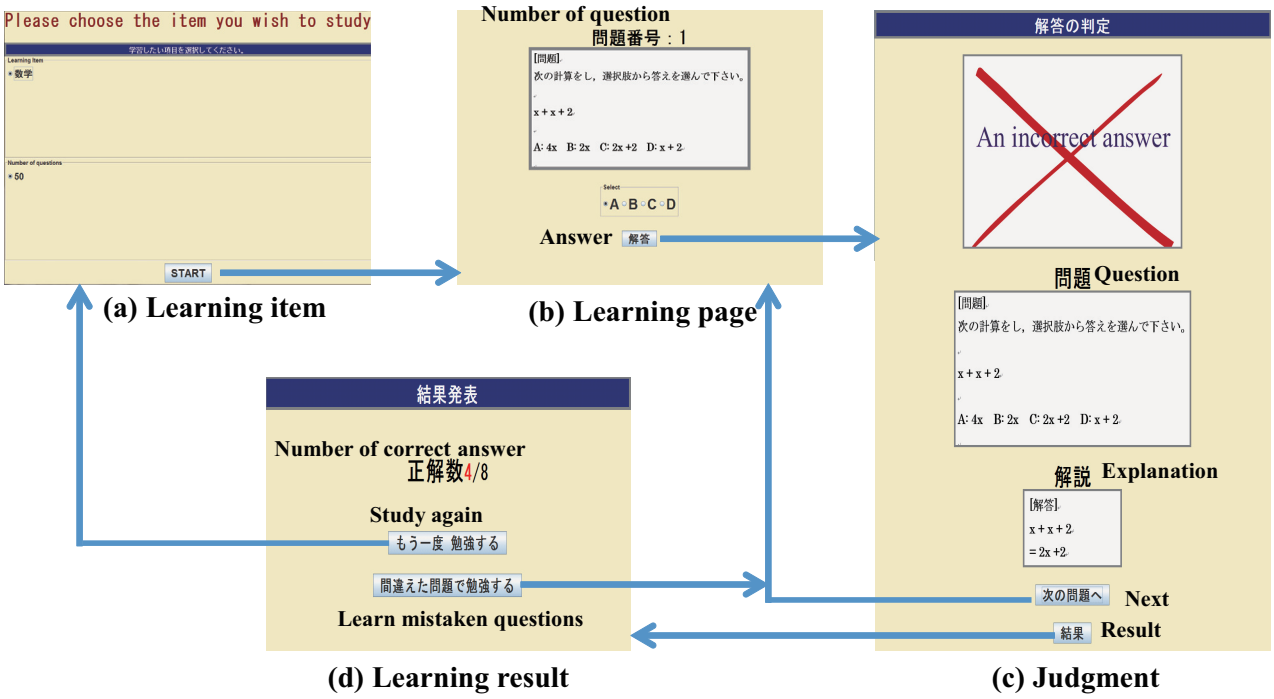


Fig. 3. Mathematics learning system.

recognition. Instead, the robot acts in accordance with the screen of the learning system (**Fig. 3**).

4.2. Learning System

We developed the learning system to help students learn mathematics (**Fig. 3**). The learning system presented a set of 50 mathematics problems at the junior high school level, which were created by consulting the "Chugaku Gakusyu Saito (in Japanese)" [a].

First, learners enter their account number to log in. A menu of study items (mathematics problems) is then displayed, with a column for the user to select the number of questions beneath it (**Fig. 3(a)**). When the learner selects "50," 50 problems are displayed at random. This enables learners to solve the problems within the selected study item one by one. Once the learner selects the study item and the number of problems, the learning screen (**Fig. 3(b)**) appears and the learning process starts. The learner provides an answer to each problem from the selection list. After an answer is given, the system displays whether it is correct, as shown in **Fig.3(c)**. When the learner selects "Next" (**Fig. 3(c)**), the system moves on to the next problem. When the learner selects "Result" (**Fig. 3(c)**) or solves all the problems, the system continues to the results page (**Fig. 3(d)**), which displays the number of correct and incorrect answers. When the learner selects "Study again," the menu of learning items is displayed (**Fig. 3(a)**). When the learner selects "Study mistaken problems," the study page presents the problems that were answered incorrectly (**Fig. 3(b)**).

The experiment was conducted in a cramming school "KIP Shingaku Kyoushitsu" [b] for junior high school students. The basic time of the first question in the first learning section was set to 240.0 s by meeting with teachers of the cramming school [b].

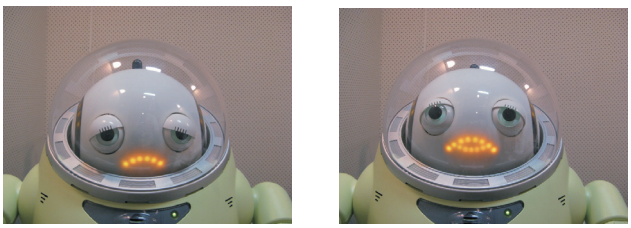
4.3. Robot's Action

4.3.1. Actions when the System Presents a Question

To enable collaborative learning, involving robots and learners alternately solving problems, constructive interactions [17, 18] are considered, which occur as two (or more) people struggle to solve difficult problems using a process wherein an idea provided by one member would encourage the other members to constructively generate further ideas. Moreover, a previous study [17] reported that constructive interactions also occur when students alternate between the roles of "speaker" and "listener," where the speaker is defined as the student who proposes a method of solving problems to their partner and subsequently solves the problems, and the listener is defined as the student who focuses attention on their partner-the speaker.

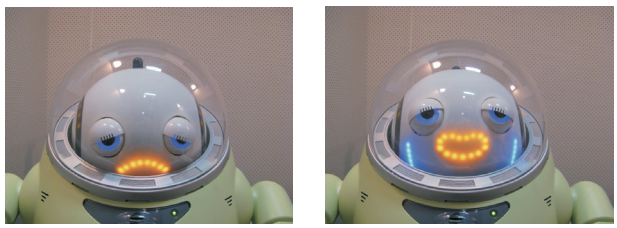
We focused on scenarios in which the roles of speaker and listener alternated between users. We found that a robot that alternates between speaker and listener roles can prompt college students to learn by alternately solving problems with the robot, which may achieve the same effect as collaborative learning between two college students [4]. Thus, the robot in this study was designed to alternately perform the speaker role and the listener role according to the previous study [4].

1. Speaker actions:
   When a human learner solves a problem, they need



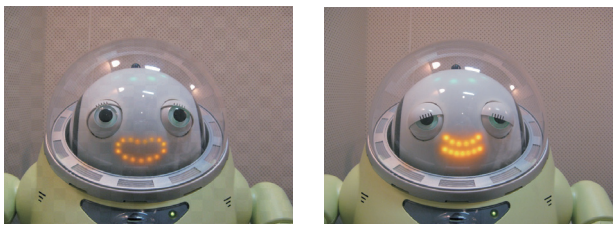
Consideration expression 1 Consideration expression 2

Fig. 4. Examples of robot expressions showing consideration for the learner.



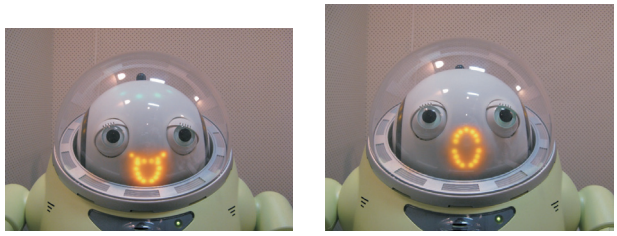
sad expression (weak) sad expression (strong)

Fig. 6. Examples of expressions of sad.



Speaking expression 1 Speaking expression 2

Fig. 5. Examples of robot expressions when speaking to the learner.



joy expression (weak) joy expression (strong)

Fig. 7. Examples of expressions of joy.

to think and often does not provide an answer for a minute or more. Therefore, during this time, the robot, playing the role of the speaker, is designed to display a considerate expression (see **Fig. 4**) accompanied by a horizontal shaking or tilting forward by its head. At the same time, the robot utters statements such as "It is my turn" and offers solutions to the problem. While explaining the solution, the robot moves its mouth using the speaker expression (see **Fig. 5**) and begins statements with "The answer of this is . . . ." However, the answers provided by the robot are not always correct. The accuracy rate of the robot's solutions is initially set to 20% but gradually increases (in 20% increments) to 100% as the learning process progresses

2. Listener actions:
   In collaborative learning sessions involving two learners alternately solving problems, the learner not answering the question often assumes a thoughtful expression as they watch their partner solve the problem. Therefore, in the listener mode, the robot first displays a considerate expression, as shown in **Fig. 4**, accompanied by a statement such as "It is your turn" or "This question is difficult." The considerate expression can be made in five forms; in listener mode, the considerate expression is pseudo-randomly selected from five types of considerate expressions, with an additional rule to avoid repeating the same expression that was selected in the previous round.

4.3.2. Actions when the System Presents a Judgment

When the learning system presents the judgment of a user-given answer, the robot sympathizes with learners by expressing an emotion according to the proposed method. Examples of the robot's 24 expressions (12 strong and 12 weak) that corresponded to each emotion in the proposed method are shown in **Figs. 6** and **7**. These expressions are designed such that user perceives the robot's emotion such as happy, joyous, sad, among others, as in a previous study [19].

Moreover, the robot was designed to make one of 12 happy or one of 12 unhappy utterances each time a learner solved a problem. Each utterance corresponded to an emotion in the proposed model. For example, the robot uttered "Yes, the answer was right" for "happy" and "Oh no! Better luck next time" for "sad." It is expected that these actions would make a learner feel as if they are learning along with the robot. A preliminary experiment was conducted with 10 college students to investigate whether students felt that the robot's utterances appropriately corresponded with the expressed emotion.

5. Experiment

5.1. Method

This experiment evaluated whether the test subjects were able to learn the learning contents. For this purpose, the subjects were divided into three groups. In the proposed method group, the subjects learned while the robot expressed emotions according to the proposed method. In the comparative-method group, the subjects learned while the robot expressed random emotions. The emotions expressed by the robot were identical in the comparative and proposed method groups. When a subject correctly answered the question, the robot expressed a random emotion from the pleasure end of the pleasure-displeasure

axis in **Fig. 1**. Conversely, when the subject incorrectly answered the question, a random emotion was selected from the displeasure end of the pleasure-displeasure axis in **Fig. 1**. In both the proposed- and comparative-method groups, the robot alternated between speaker and listener actions. In the third group, i.e., the control group, two human subjects learned together.

The previous study reported that a robot, which expressed emotions according to the sympathy expression model, promoted more intimacy and sympathy for college students than the model, which used one emotion vector to express emotions in a collaborative learning [20]. The effect, however, was no difference between the sympathy expression model and the model which expressed a random emotion from the pleasure end of the pleasure-displeasure axis as shown in **Fig. 1**. Therefore, this study compared the sympathy expression model with the model which expressed a random emotion.

Thirty two junior high school students at "KIP Shingaku Kyoushitsu" [b] which is a cramming school for junior high school students were recruited for the study. The teacher of KIP Shingaku Kyoushitsu reported that the learner's school records are at the middle stage. The learners were divided into three groups so that the learner's school records are even according to teacher's comments. 12 subjects (6 boys, 6 girls) were assigned to the proposed model group. Another 12 subjects (4 boys, 8 girls) were assigned to the comparative model group. The control group comprised 10 subjects (4 boys, 6 girls). The subjects were asked to learn mathematical topics using the learning system (see **Fig. 3**) for 40 min every day for five days. An experimenter timed the sessions from a separate room, beginning from the time at which the learning system presented the first question. After 40 min, the experimenter entered the experiment room and informed the learner that the session was finished.

The subjects in each group were requested to alternately solve the questions with the robot or the partner learner. To investigate the associations between the subject-partner pairs in each learning session, the learning process was recorded.

5.2. Evaluation

The results for each group were evaluated by three criteria. The first criterion was improvements in the test score, which was obtained by subtracting the pre-test score from the post-test score. The pre- and post-tests were conducted before starting the experiment and five days after finishing the experiment, respectively, and each comprised 50 problems selected from the learning system.

The second criterion was a subjective metric based on a questionnaire evaluation. The questionnaire asked subjects to write freely about their experiences during the experiment and was distributed to the proposed-model and comparative-model groups.

The third criterion was the neglect rate, which was a more objective metric, and was obtained by analyzing the video recordings of the proposed and comparative model groups during the learning sessions. Although the robot's actions were in accordance with the screen of the learning system, the system was operated by the learners, who could therefore ignore the robot performing the speaker action and answer questions faster than the robot. Thus, we defined neglect as a learner ignoring what the robot was saying during the speaker actions and instead answering the question before the robot. Accordingly, the neglect rate was defined as the rate at which neglect occurred during one learning session.

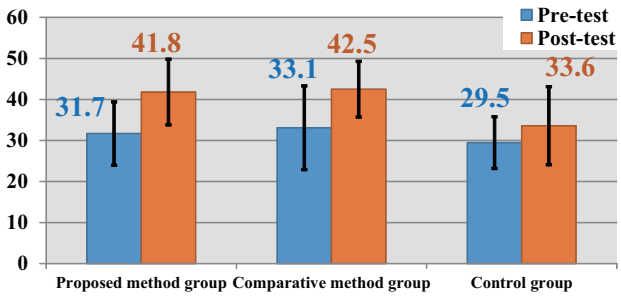


Fig. 8. Average test scores of each group in the pre and post-tests.

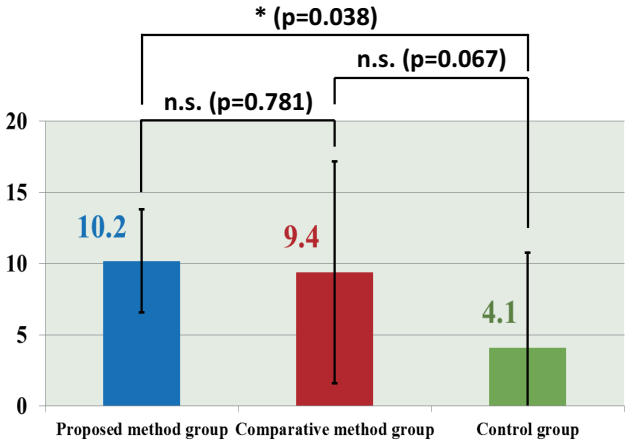


Fig. 9. Average score improvement of each group.

5.3. Results

5.3.1. Score Improvement

The average pre- and post-test scores for each group and the average score improvement for each group are shown in **Figs. 8** and **9**, respectively. The error bars in **Figs. 8** and **9** indicate the standard deviation. The pre-test scores did not differ significantly among the three groups, indicating that the subjects in each group had similar prior knowledge of the learning content. As shown in **Fig. 9**, the score improvement was higher for the proposed-method group than for the other groups, while the score improvement was higher for the comparative-method group than for the control group. To determine the effectiveness of mathematics learning in terms of the score improvement a Tukey-Kramer test was applied to

the data [21]. The results revealed a statistically significant difference between the proposed-method and the control group (see **Fig. 9**), suggesting that subjects in the proposed-method group learned more effectively than the subjects in the control group.

5.3.2. Questionnaire

First, the responses to the questionnaires from the proposed-method group are examined. The subjects provided comments such as "The robot makes a lot of expressions. Its explanation is intelligible when it solves the question;" "The robot felt sad, like I did, when I made mistakes. It felt happy, like I did, when I correctly solved a question;" "The robot expressed rich facial expressions and reflected my delight when I solved the questions. Therefore, I enjoyed learning with the robot;" "Although I solved the questions quickly, the robot was very slow in solving the questions;" and "The robot's tone of voice stayed constant. Therefore, I was bored while learning alongside the robot." These subjective responses suggest that the subjects had positive impressions of the collaborative learning experience with a robot that reflected their emotions per the proposed method. However, some subjects reported negative experiences such as the robot being too slow to solve the questions and its voice being monotonous.

Next, the responses on the questionnaires from the comparative-method group were analyzed. Some responses given by subjects were "When I solved the questions correctly, the robot expressed happy emotions. When I could not solve questions correctly, the robot expressed sad emotions;" "I preferred learning with the robot to learning alone;" "The robot tended to repeat the same expressions. Therefore, I was bored while learning alongside the robot;" "The robot could not sympathize with me. I ignored the robot's speech during the collaborative learning." These responses suggest that subjects in the comparative-method group gained the same positive impressions as the subjects in the proposed-method group. However, the subjects quickly became bored and ignored the robot's speech because the emotions it expressed did not vary.

5.3.3. Neglect Rate

The average neglect rates measured for the proposed- and comparative-method groups are shown in **Fig. 10**. **Figs. 11** and **12** show the score improvement measured for each of the learners in the proposed- and comparative-method groups. **Figs. 13** and **14** show the neglect rate during the fifth learning session for each learner of the proposed- and comparative-method groups. In the first study session, the neglect rate was under 12.2% in both groups (**Fig. 10**). The neglect rate in both groups increased after the second session as the subjects' learning progressed. In the comparative method group, the neglect rate exceeded 55% during the second learning session and increased to 82% during the last learning session. This suggests that subjects in the comparative-method group ignored the robot and learned by themselves. On the contrary, the increase in the neglect rate occurred more slowly in the proposed-method group compared with the comparative-method group. Specifically, the neglect rate in the proposed-method group was below 50% in the second, third, and fourth sessions. Even in the last session, the neglect rate increased to only 53%.

This result suggests that learners in the proposed method group continued alternating the roles with the robot, whereas learners in the comparative method group tended to abandon this interaction. The previous study re-

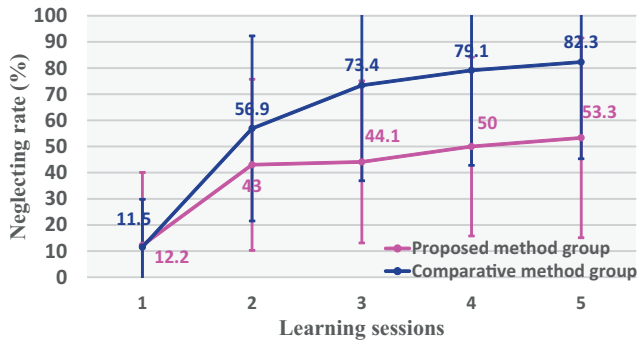


Fig. 10. Average neglect rate.

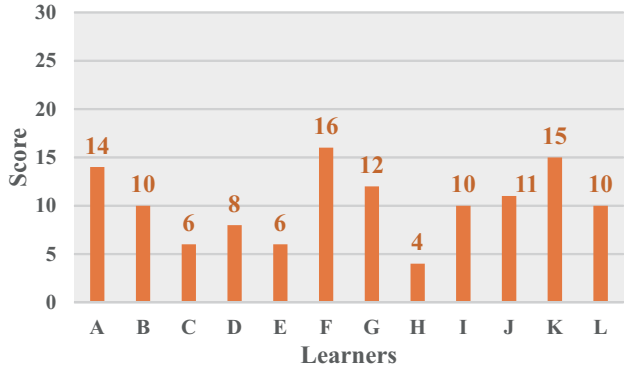


Fig. 11. Score improvement for each learner of the proposed method group.

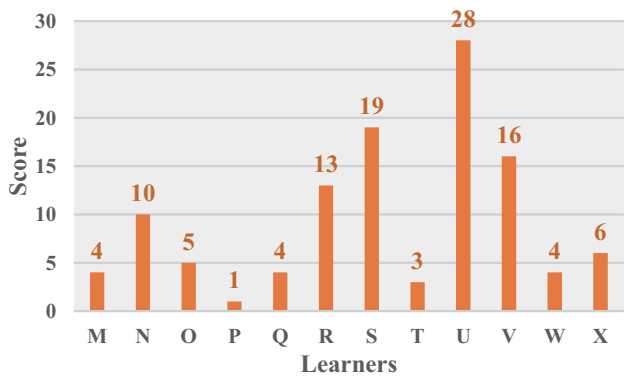


Fig. 12. Score improvement for each learner in the comparative method group.

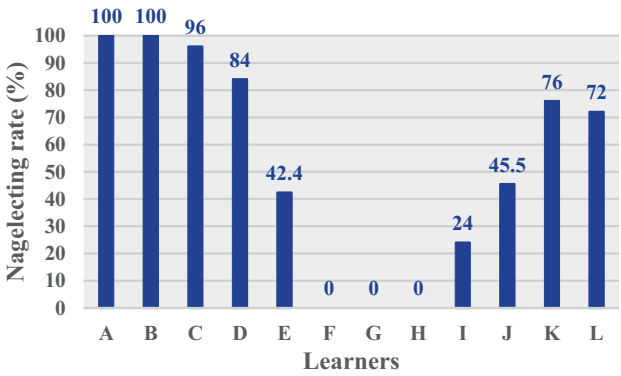


Fig. 13. Neglect rate during the fifth learning session for each learner of the proposed method group.

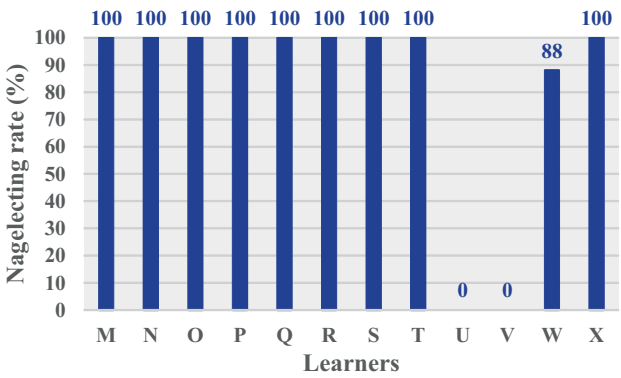


Fig. 14. Neglect rate during the fifth learning session for each learner in the comparative method group.

ported that the collaborative learning, which learners alternately solve questions with the robot, can prompt college students to improve their learning effect [4]. We think that same learning effect occurred in this experiment. Therefore, no variation occurred in each learner's score improvement of the proposed model group than the comparative model group (**Figs. 11** and **12**).

Moreover, we considered why high score improvement of comparative method group was obtained for learners S, U, V. The neglect rates of learners U and V in the fifth learning session were 0%. Thus, it can be speculated the learners U and V alternately solved the question with the robot. Additionally, the correlation coefficient was -0.3 between score improvement and learners (F, G, H, I, U, V) with neglect rate of the fifth learning session less than 30%. Thus, learners, who did not neglect the robot and alternately solved the questions with the robot, tended to have some of the most substantial improvements in their scores in both the proposed and comparative method groups.

However, the difference of score improvement cannot be analyzed between learners U, F and H by collecting data of this experiment. In future work, learner's learning motivation and impression on the robot will be investigated and the relationship with learning effect will be clarified.

6. Discussion

Based on the study results, collaborative learning with a robot that alternates problem-solving roles with a human learner and meanwhile expresses emotions according to the proposed method is more effective than collaborative learning between two junior high school students. Moreover, we found that learners alternated roles with the robot which expresses emotions according to the proposed model while solving mathematical problems. In contrast, learners interacting with a robot expressing random emotions did not alternate the problem-solving role as often. Therefore, enabling an educational-support robot to reflect the emotions of learners can mitigate the problem of users becoming disengaged with the robot during collaborative learning.

The score improvements for the subjects after learning by the proposed method were higher than those of the control group. The control group had a low score improvement because based on observations from the videos of the control group, the learners alternately solved the problems in the first learning session but had a tendency to continue talking rather than solving problems as learning progressed. Moreover, some pairs in the control group did not alternately solve the problems; instead, all questions were answered by a single subject while the partner only looked at the questions. Conversely, in the proposed-method group, the robot alternately performed the speaker and listener roles, which encouraged the human partner to follow this behavior. In fact, one student reported, "The robot alternately solved the problems. Therefore, I learned properly in each learning session." Moreover, the robot explained the method to find the solution when playing the speaker role. Thus, listening to the robot during the collaborative learning sessions helped the students to understand how each problem was solved. Moreover, the learners in the proposed- and comparative-method groups might have been helped additionally by the robot having an 100% accuracy rate in the fifth learning session.

Results demonstrated that under the proposed method, the robot expressing emotions according to the proposed model promoted alternative problem solving by the subjects for a longer period of time than the robot expressing random emotions. In contrast to the comparative method, in the proposed method, the emotion vector was adjusted to suit the answer time of the subjects. In the early sessions, the subjects required a relatively long time to solve the questions. Therefore, the emotion vector of the proposed method moved toward the sleep end of the arousal-sleep axis, and the robot expressed "sleepy" emotions. As the answer time of the subjects shortened while the learning process progressed, the emotion vector moved toward the arousal end of the arousal-sleep axis. In this way, the emotion vector implemented in the proposed method allowed the robot to adapt to the subjects' respective learning situations. Although the robot using the comparative method expressed a random emotional response which was the pleasure end or the displeasure end of the pleasure-displeasure axis; corresponding to a cor-

rect or incorrect answer, the subjects in the comparative model group did not perceive sympathy from the robot. Therefore, they ignored its verbal prompts and responses and learned independently.

7. Conclusion

Here, we proposed a sympathy-expression model to enable educational-support robots to sympathize with learners. Our study relied on Russell's circumplex model of affect [8], in which an emotional state is described in two dimensions: pleasure-displeasure and arousal-sleep. The proposed method uses two emotion vectors to express emotions that sympathize with the learner's emotions: the correct emotion vector represents the emotions of a robot when the answer is correct, whereas the incorrect emotion vector represents the emotions corresponding to an incorrect answer. Moreover, the lengths and angles of the emotion vectors are adjusted according to the number of correct answers and the time the user takes to answer. Thus, the proposed model can be used to enable the robot to express multiple emotions and sympathize with learners depending on their learning situation.

An experiment was conducted to test the robot in a collaborative learning scenario in which the robot alternately solved questions with junior high school students. This results of the experiment indicate that the collaborative learning with a robot which alternately solves questions with a human and simultaneously expresses emotions according to proposed method promotes more learning than collaborative learning between two junior high school students. Moreover, the learners alternately solved questions with the robot that used the proposed method and followed this collaborative-learning process for a longer period of time than with the robot which expressed emotions in a random order. Therefore, the robot which expresses emotions according to the proposed method can address the issue of learners ignoring educational-support robots as the learning process progresses.

To improve upon the proposed model, we are currently focusing on the robot's utterances during the collaborative learning with human learners. We will further investigate the effect of changing the robot's accuracy rate as learning progresses. In this way, we will determine the correlation between the neglect rate and other learner characteristics to elucidate the factors that cause learners to neglect the robot during collaborative learning. Moreover, the learning effect was compared between the sympathy expression model and many other models which expressed the emotion according to multiple rules.

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